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Occupational structure, technological innovation, and reorganization of production ☆

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Abstract

Recent studies have found evidence for the complementarity between white-collar labor and technological capital. However, the estimated elasticities appear too small to explain the observed changes in labor occupational structure. Most of the increases in the share of white-collar employment have been concentrated during recessions, but aggregate investment in technological capital seems procyclical. We examine several potential explanations for this puzzle using a panel of Spanish manufacturing firms that provides highly disaggregated information on employees by occupation. The empirical results show that the decision of adopting new technologies by new innovative firms is countercyclical, and has a much stronger effect on occupational structure than the accumulation of technological capital by old innovative firms. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

Recent empirical studies using either industry-level or plant-level data from several OECD countries have found significant complementarities between new technological capital and white-collar labor (see Berman et al., 1994; Machin, 1994; Dunne et al., 1995; Machin et al., 1996, among others). This result supports the hypothesis, stated as skilled-biased technological change, that the main factor explaining the shift in relative demands for different labor inputs has been the reduction in the price of new technological capital and its complementarity with white-collar labor.[1] However, another common result from these studies is the small elasticities of the demand for white-collar labor with respect to capital and, specially, technological capital. These elasticities explain only a small proportion of the secular and cyclical variation in the proportion of white collar workers, which remains characterized by unobservable factors. This result raises the question of what these unobservables represent.

More recently, some studies suggest that technological change within firms appears together with deep processes of reorganization of production (see Brynjolfsson and Hitt, 1998; Bresnahan et al., 1998). The argument is that technological capital by itself does not yield significant benefits unless the firm performs global changes in production organization. Such changes involve a new organization of the workplace, which is usually complementary with high skill workers (see Aghion and Howitt, 1994). In principle, this hypothesis may explain the small elasticities between changes in occupational structure and technological capital that have been found in previous studies. In particular, the qualitative decisions of introducing new capital inputs may imply a deep reorganization of the production process, which can imply a stronger effect on occupational structure than a simple increase in the stocks of such capital inputs. Once the reorganization of the workplace has been implemented, increasing the amount of technological capital might have relatively small effects on the occupational structure of the firm.

In this paper, we use a panel of Spanish manufacturing firms between 1986 and 1991 with highly disaggregated information about labor and capital inputs to evaluate the importance of alternative explanations to changes in occupational structure and their relation with technological change. The availability of firm-level panel data with a high disaggregation by occupation allows to obtain more robust evidence for some empirical results in the literature. We exploit these data to evaluate to what extent aggregation can be responsible for the empirical puzzle. In addition, we evaluate the importance of the alternative explanation of *reorganiza-*

[1] The empirical evidence until now has been based on the distinction between white-collar and blue-collar labor, which are also typically labeled as skilled and unskilled labor. This is the reason why such evidence is interpreted as *skilled-biased technological change*.

tion of the production process.[2] We postulate that the decision to introduce, by first time, a new capital input into the production process may have different implications on occupational structure than the decision to rise the stock of that input once it has been installed.

Our dataset contains firm-level annual information on the number of permanent workers by five occupations (managers, professionals, commercials, clerical workers, and blue collar workers), the number of temporary workers, physical capital, investment on R&D and purchases of technological capital externally generated to the firm. While other datasets just report aggregate data on white collar employees, our dataset breaks down white collars into four occupations. This allows us to distinguish the demand patterns for these occupations. Our empirical analysis is based on the estimation of equations for the occupational shares in permanent employment that include physical and technological capital as explanatory variables, as well as indicators on the innovative status of the firm.

The estimation results discussed in section 4 can be summarized as follows. The estimated demand elasticities for labor inputs with respect to physical and technological capital inputs are positive for white-collar inputs. However, the elasticities with respect to R&D and technological capital are very small and insignificant, with the same order of magnitude as the ones obtained by Dunne et al. (1995) for the US. By contrast, the adoption of new technological capital has a very strong effect on occupational structure: in particular, whereas the effect of introducing technological capital is strongly positive for commercials, we find the opposite effect for blue collars. In addition, we find a large persistence in the demands for labor inputs. Our results yield evidence in favor of the hypothesis that, at the firm level, changes in occupational structure have been mainly implemented in accordance with qualitative changes in the organization of production. This finding supports the hypothesis of reorganization of production as the leading explanatory factor for the observed changes in occupational structure.

The rest of the paper is organized as follows. In section 2, we give a brief review of the previous empirical literature, in order to characterize the empirical puzzle, and consider the alternative explanations to this puzzle, ending with informal evidence about the features behind the restructuring processes in Spanish manufacturing.

Section 3 presents preliminary evidence about the joint reorganization of the workforce and the production process. We show that those firms that adopted new technological capital between 1986 and 1991 (16.5% of the firms in the sample)

[2] Brynjolfsson and Hitt (1998) and Bresnahan et al. (1998) use qualitative information about firms' adoption of new working methods. This information is very rarely available in most firms' datasets. However, it has other type of limitations. In particular, it is a cross-section with less than 380 firms. As these authors acknowledge, the correlations in their study are "largely driven by cross-sectional differences between firms," and "there is very limited evidence regarding the effects of changes over time in the variables of interest" (Bresnahan et al., p. 18).

have been the ones with the most intense changes in occupational structure. They are responsible for more than 50% of the net creation of professional jobs, and for more than 30% of the net creation of commercial jobs.

Our empirical concern, that we address in section 4, is the effect of the introduction of new capital inputs on occupational structure. We estimate conditional demand equations for labor and capital inputs where the decision to adopt new technological capital can imply a deeper restructuring process within the firm than a simple increase in the stock of an existing input. Furthermore, we account for dynamics and feedback effects among labor and capital inputs. Finally, Section 5 concludes.

2. Basic framework and alternative hypotheses

2.1. Previous studies

In this subsection, we provide a short review to the earlier empirical evidence on the determinants of occupational composition of employment. The typical specification in previous empirical work that study technology–skill complementarity has been the following (see Berndt et al., 1992; Berman et al., 1994; Machin, 1994; Dunne et al., 1995; Machin et al., 1996, among others):

$$\ln s_{it} = \beta_0 + \beta_w \boldsymbol{w}_{it} + \beta_K k_{it} + \beta_R r_{it} + \beta_Y y_{it} + u_{it} \tag{1}$$

where $s_{it} = L_{it}^{\mathrm{WC}} / L_{it}$ is the share of white-collar employment in total employment; $\boldsymbol{w}_{it}$ is the logarithm of the wage rate; k_{it} and r_{it} are the logarithms of the stocks of fixed capital and technological capital; and y_{it} is the logarithm of output. As explained by Bond and Van Reenen (1998), this specification can be interpreted as a short-run cost-minimizing input demand equation, where some direct measure of technical progress, which is assumed to be exogenous, is used. This equation can also be interpreted as the difference between the conditional demand for white collars and the conditional demand function for total employment. This representation may be obtained by inverting the demands for capital inputs with respect to their prices, and substituting such capital input prices in the conditional demands for labor inputs. The specification implicitly assumes no adjustment costs for labor, and no discontinuities after the adoption of new technology.[3]

Table 1 summarizes the estimation of Eq. (1) for some studies. First, notice that the elasticities with respect to physical capital (or, in some studies, capital equipment) tend to be significantly larger than the elasticities with respect to

[3] Previous studies using micro datasets (e.g., Dunne et al.) estimate this equation using the subsample of firms who invest in R&D.

Table 1
Estimated elasticities for physical capital, R&D, and real output. Dependent variable: logarithm of the share of white collars in total employment

Article	Country	Data	Estimation method	Elasticity capital	Elasticity R&D	Elasticity output
Estimates from previous studies						
Berndt et al. (1992)[a]	US	two-digit industries 1976–1986. ASM[b]	OLS in levels	0.054 (0.016)	0.014 (0.006)	−0.054 (0.016)
Dunne et al. (1995)[c]	US	Plant level data 1972–1988. ASM	IV First differences	0.012 (0.007)	0.007 (0.003)	−0.044 (0.008)
Machin et al. (1996)[d]	US	two-digit industries 1973–1989. STAN[e]	OLS First differences	0.068 (0.014)	0.013 (0.007)	−0.029 (0.007)
	UK	two-digit industries 1973–1989. STAN	OLS First differences	0.029 (0.013)	0.018 (0.007)	−0.005 (0.007)
	Denmark	two-digit industries 1973–1989. STAN	OLS First differences	0.016 (0.013)	0.041 (0.013)	−0.068 (0.009)
	Sweden	two-digit industries 1973–1989. STAN	OLS First differences	0.034 (0.012)	0.025 (0.012)	−0.006 (0.005)
Estimates from Spanish CBBE data						
		Firm-level data 1986–1990 CBBE	OLS First differences	0.004 (0.006)	0.002 (0.001)	−0.006 (0.004)
		two-digit industries 1986–1990 CBBE	OLS First differences	0.007 (0.024)	0.015 (0.009)	−0.038 (0.040)

Standard errors are in parentheses.
[a] In Berndt et al., High-tech capital is considered instead of R&D.
[b] ASM is the Annual Survey of Manufacturers from the US Census Bureau.
[c] Dunne et al.: Table 11.
[d] Machin et al.: Table 5(b).
[e] STAN is the Standardised Analytical Database, compiled by the OECD.

R&D and new technological capital. This result seems at odds with the hypothesis of technological change biased towards white-collar labor. Second, the elasticities with respect to real output are always negative and, in several cases, significantly larger than the elasticities with respect to capital inputs. Finally, the elasticities with respect to physical capital and, specially, with respect to R&D and new technological capital are too small to account for the important increases in the dependent variable during the sample periods used in these studies. That is specially the case for Dunne et al. (1995), which is the only study that uses data on individual firms.[4] In the last panel of the table, we have replicated the estimates using our Spanish firm-level dataset (that will be described below), obtaining similar results, which are not altered when we aggregate data into two-digit industries.

2.2. Alternative explanations

Here, we consider several complementary explanations to the previous puzzle. The first and most obvious explanation is that the estimated elasticities are downward biased due to the existence of measurement errors in the capital variables. However, although the existence of measurement errors is quite plausible when using micro data, its incidence should be much lower when using industry-level data. In addition, measurement errors cannot explain why the elasticities with respect to new technological capital are significantly smaller than the elasticities with respect to physical capital (unless we are willing to accept the very unlikely hypothesis that the measurement error in new technological capital is more severe than in physical capital). Nonetheless, from a simple analysis of the data it can be seen that the main reason behind the small elasticities is that while firms tend to invest more in capital inputs when they face positive productivity shocks, the largest increases in skilled labor have occurred when firms experience negative shocks (see Dunne et al., 1995, and section 3 below). It seems therefore difficult to explain this fact in terms of measurement errors.

A second explanation for the puzzle is that most of the reduction in blue-collar employment has to do with the increasing competition in international trade from emerging economies, where unskilled labor is cheaper, and not with the introduction of new technological capital. This competition may have decreased the participation in total output, and consequently in total employment, of industries that are intensive in production labor. The main empirical implication of this hypothesis is that the main source of changes in occupational structure should be between industries, due to employment reallocation from those industries suffering the effects of international trade. This evidence have been evaluated by Berman et

[4] The OLS estimates in Dunne et al., 1995 present even smaller values for the elasticities with respect capital inputs.

al. (1994) and Dunne et al., 1995 for the US, and Machin et al. (1996) for other OECD countries, finding that international competition has, at most, a second-order effect on occupational structure. In Section 2.3, we will confirm such evidence for our Spanish dataset.

A third potential explanation is that skill-biased technological change is a consequence of the combination of new technological capital and a deep reorganization of production at the individual firm level (see Brynjolfsson and Hitt, 1998; Bresnahan et al., 1998). In particular, the qualitative decisions to introduce new capital inputs may imply a deep reorganization of the production process, and therefore their effect on occupational structure may be stronger than the marginal decisions to increase the stock of already existing inputs. Once the reorganization of the workplace has been implemented, increasing the amount of technological capital might have small effects on occupational structure. The most important effect of technological capital on the demand for skilled labor would be captured by qualitative variables indicating discontinuous response of demands when new technological capital is adopted. If that is the case, estimations that do not recognize this discontinuous shift will provide downward biased estimates of the complementarity between labor inputs and new technological capital.

A particular case for this reorganization of production is the outsourcing of certain routines that were formerly involved in the production process. The idea is that, in order to reduce costs, firms could decide to externalize certain production tasks that were previously embedded into the production process. The goods and services generated by such production tasks are then bought to other firms that are specialized in those tasks. However, outsourcing might not necessarily result from the adoption of new technologies. For instance, changes in consumers' preferences towards more diversified high-quality products can induce firms to specialize in the final stages of the production and distribution process.

Finally, another explanation builds on the existence of non-homotheticicities in the production function. The optimal occupation mix may depend on the level of output. In other words, the effect of real output on the conditional factor demands can be different for skilled and unskilled occupations. This is consistent with the estimates presented in Table 1. If the non-homotheticity of the production function operates only for relatively large levels of output, and if large firms have suffered a negative trend in their market shares (e.g., as the result of market deregulation and increasing competition), this hypothesis might explain part of the secular changes in occupational structure.

2.3. Innovation and restructuring in Spanish manufacturing

There exists important evidence of production restructuring and outsourcing in Spanish manufacturing in the 1980s and 1990s, which appears closely related to the adoption of new technologies. In this subsection, we give three particular examples on three manufacturing industries: paper edition, electric material and electronic, and textile and footwear.

The industry of paper edition has lived a strong production restructuring at several levels (see Redondo, 1999). First, firms have developed quality-oriented strategies to face increasing competition, which have been caused by two interrelated phenomena: the widespread access to cheaper electronic technologies for paper edition, and a change of the customer–seller relationship, in favor of customized instead of standardized products. Second, firms have specialized their production process, increasing the degree of complementarity of their production tasks in order to capture productivity improvements and increase the efficiency in the use of the new technologies. Such specialization has led firms to externalize some production tasks, ordering them to other firms. In particular, there is evidence of strategic outsourcing, consisting on cooperative agreements among firms within this industry, which specialize in different stages of the paper edition process.

The electric material and electronic industries in Spain faced a process of market liberalization in the 1980s. Given the large degree of specifity of many production tasks in this sector, the only alternative for most firms (especially small- and medium-sized firms) was to specialize in specific production tasks, particularly on just-in-time tasks, in order to reduce operating costs. The cost of adoption of new technologies was lowered thanks to the specialization. Suárez-Villa and Rama (1998) find that firms' specialization originated a significant transfer of labor force within the firms from those externalized production tasks to activities of innovation and marketing research. Most of the innovation generated by these firms consist of process innovations, which, in turn, have increased the demand for highly qualified labor.

Other interesting example of outsourcing and production restructuring concerns the textile and footwear industry, which lived a deep crisis in the mid-1980s because of the increasing competition from developing countries after the dollar depreciation. Since then, surviving firms and entrant firms have evolved from vertical integration (from basic production to final distribution) to the outsourcing of many production tasks. An interesting example is the Spanish footwear company Panama Jack, founded in 1982, which has outsourced all the manufacturing activities except final packing (see Dinero, 1996). In turn, it has concentrated on product innovation (that includes design, product presentation, and marketing strategies), but also on process innovation, organizing the production stages among the different suppliers while maintaining the control of the final product, the R&D and market research activities, and the product distribution. The importance of blue-collar employment has been reduced in favor of other occupations that are more complementary with product design and market distribution, such as managerial, professional, and commercial positions.

Finally, there is an important case for outsourcing within the country that has affected all the manufacturing industries, linked to the development of the services sector. Hermosilla (1997) shows that in the last two decades most manufacturing firms have tended to hire external services to specialized companies, instead of producing them within the firm. In 1993, about 19% of the total costs in manufacturing corresponded to supply of external services. In the same year, more than 60% of manufacturing companies buy some service activity to external firms. To this matter, Collado (1994) states that the those occupations that are more related to service activities, such as clericals, tend to be reduced in manufacturing firms as they externalize tasks linked to services.

From the available evidence, it is clear that outsourcing of production is a very important phenomenon that takes part in the reorganization process of firms. However, although firms tend to externalize certain tasks that may consist on manufacturing or services activities, they still tend to maintain the control of R&D and selling activities, due to the strategic importance of these activities.

3. Trends in the occupational structure of Spanish manufacturing employment

3.1. The data

The main dataset consists of a panel of 1080 manufacturing firms collected from the database of Central de Balances del Banco de España (CBBE), which remained in the sample every year between 1986 and 1991. This dataset was already used by Alonso-Borrego (1999) to estimate a labor demand model for blue collar and aggregate white collar workers. The criteria for selection of the sample and construction of the variables used in the empirical analysis (market value of the capital stocks, wages, etc.) are described in the Appendix A.

One of the main limitations of this dataset for the purpose of this paper is that it does not provide disaggregated information of temporary employment by occupation. There, we only have the number of temporary employees within the firm during the year, and the average number of weeks worked for the year, so that we calculate temporary employment in annual terms as the number of temporary employees times the average number of weeks worked for the year. A potential criticism to the empirical evidence based on this sample is that the observed changes in occupational shares in permanent employment can merely reflect a contract switch, from permanent to temporary, and therefore the occupational structure of total employment may have remained unchanged. In order to shed some light on this issue, we will also make use of the information based on the Spanish Labor Force Survey (Encuesta de Población Activa [EPA]). The EPA is a large micro dataset that reports information about more than 100,000 individuals on a quarterly basis. We concentrate on the second quarters of the EPA from 1987 to 1992.[5] In order compare the occupational distribution and its trend with the

[5] The second quarter contains detailed information on the labor market status of the individuals, such as occupation, contract duration, etc.

CBBE sample, we use for each year the EPA subsample of dependent employees working in manufacturing industries.

3.2. The evolution of occupational structure

In Table 2, we present the occupational shares and their changes during the period. In the upper panel, we present this information for permanent employment in our CBBE sample of 1080 firms from 1986 to 1991, and in the lower panel, we report the same decomposition by type of contract based on the EPA. We have also included the proportion of temporary employment in total employment in both CBBE and EPA datasets. We can see that although the distribution of employment by occupation and its evolution is not independent of the type of contract, the changes in the occupational structure of permanent employment have not been offset by opposite changes in temporary employment.

By comparing both datasets, we can see that the occupational shares are quite different, with permanent blue-collar employment being much more important in the EPA sample. This reflects the fact that the CBBE sample over-represents large- and medium-sized firms, which have a lower proportion of permanent blue collar employees. Moreover, temporary employment is relatively less important in

Table 2
Shares in employment (%) by occupation and type of contract (change during the period in parentheses)

CBBE	Permanent	
Blue collar	66.01 (−3.77)	
White collar	33.99 (+3.77)	
Managers	1.97 (+0.23)	
Professionals	11.34 (+1.80)	
Commercials	7.33 (+1.32)	
Clericals	13.34 (+0.42)	
Proportion of temporary employment	5.55 (+4.67)	
EPA	**Permanent**	**Temporary**
Blue collar	80.75 (−3.49)	88.22 (−4.18)
White collar	19.25 (+3.49)	11.78 (+4.18)
Managers	1.52 (+1.06)	0.26 (+0.16)
Professionals	3.86 (+1.05)	2.29 (+1.39)
Commercials	3.31 (+0.50)	2.97 (+0.24)
Clericals	10.56 (+0.87)	6.25 (+2.39)
Proportion of temporary employment	12.24 (+18.14)	

Sources: CBBE sample of 1080 manufacturing firms, 1986–1991, and EPA sample of manufacturing employees, 1987:II–1992:II.
Reference year for the distribution of employment by occupation is (end of) 1986 for CBBE and 1987:II for EPA.

the CBBE sample than in the EPA sample. However, the trends in occupational structure for permanent employment, and in the trend of temporary employment, appear to be very similar.

The primary fact from the CBBE sample consists of the large increase in the proportion of white-collar occupations in permanent employment. However, whereas this increase is unimportant in the case of clerical employment, it is high in the case of managers, and among professional and commercial workers most particularly. This fact is also apparent in the EPA sample, although the largest increases take place for managerial and professional workers. In any case, from both panels in Table 2, it is clear that the proportion of blue-collar employment did fall during the period, irrespective of the type of contract.

However, the occupational structure of temporary employment does not match the one found for permanent employment. Here the proportion of blue collar workers is much higher, although we still find a significant decrease. Furthermore, the distribution of white collar employees differs very much depending on the type of contract: we find significant differences in the relative importance of managers and commercials in white-collar employment by type of contract. In addition, we observe that the increase in the proportion of commercials is much lower for temporary workers than for permanent ones.

In order to evaluate the impact of increasing international competition on occupational structure, we present in Table 3 a decomposition of the total aggregate change in the shares of white-collar occupations. We follow Berman et al. (1994) to define three components,

$$\Delta P_t^j = \sum_{i=1}^{N} \Delta s_{it} P_{i,t-1}^j + \sum_{i=1}^{N} s_{i,t-1} \Delta P_{it}^j + \sum_{i=1}^{N} \Delta s_{it} \Delta P_{it}^j \tag{2}$$

where Δ denotes the time difference operator, $P_t^j = L_t^j / L_t$ and $P_{it}^j = L_{it}^j / L_{it}$ are the proportions of labor input j in aggregate permanent employment and in firm i, respectively; and $s_{it} = L_{it} / L_t$ denotes the weight of firm i in total aggregate employment at period t.[6] The first term measures the change in the input share due to reallocation of employment between groups. The second term measures the change in the input share due to changes in the occupational structure within groups. Finally, the third component captures the covariance between the previous two terms (i.e., the change in the input share as a result of reference groups changing both their occupational structure and their participation in total aggregate employment). As reference groups, we consider individual firms for the CBBE dataset, and in order to allow for comparison between CBBE and EPA datasets, we also consider two-digit industries. If international competition explains changes in occupational structure, we should observe that the main source of changes in

[6] The periods t and $t-1$ denote the final and initial years in the sample period, respectively.

Table 3
Between-groups variation in occupation shares (Reference groups: firms and industries)

Occupation	Source of change	Firms	Industries		
		CBBE	CBBE	EPA permanent	EPA temporary
White collar	Total change	3.766	3.766	3.489	4.180
	Between groups	0.819	0.160	0.273	0.801
	Within groups	3.496	3.552	3.100	3.304
	Covariance	−0.549	0.054	0.116	0.075
Managers	Total change	0.227	0.227	1.063	0.162
	Between groups	0.154	0.043	0.045	0.027
	Within groups	0.301	0.214	1.029	0.100
	Covariance	−0.227	−0.030	−0.011	0.034
Professionals	Total change	1.799	1.799	1.052	1.387
	Between groups	0.110	0.057	0.166	0.321
	Within groups	1.810	1.648	0.873	0.989
	Covariance	−0.121	0.094	0.012	0.077
Commercials	Total change	1.320	1.320	0.502	0.244
	Between groups	0.331	0.059	−0.031	0.213
	Within groups	0.941	1.259	0.563	0.328
	Covariance	0.048	0.002	−0.030	−0.296
Clericals	Total change	0.420	0.420	0.872	2.386
	Between groups	0.224	0.000	0.093	0.240
	Within groups	0.445	0.431	0.634	1.887
	Covariance	−0.249	−0.011	0.145	0.259

Sources: CBBE sample of 1080 manufacturing firms, 1986–1991, and EPA sample of manufacturing employees, 1987:II–1992:II.
The decomposition of the variation in the proportion of blue collar workers has been excluded for being redundant.

occupational shares should be the reallocation of employment from some groups to other depending on their sensitivity to international competition.

We can see that the descriptive evidence for the CBBE data is analogous for the two alternative reference groups. The use of industries as reference groups with CBBE data just tend to highlight the relative contribution of within-groups variation to the total change in occupational shares. The main result from this table is that within-groups variations constitute the leading source of changes in occupational structure, and therefore, the main changes in permanent employment have occurred at the individual firm or at the industry level.[7] This is particularly the case for professional and commercial workers, whose growth rates mean most of the increase in white-collar permanent employment. Although there is also a significant contribution of employment reallocation between-firms to the increase

[7] This evidence is similar to that found for the US by Berman et al. (1994) and Dunne et al. (1995), or for other OECD countries by Machin et al. (1996).

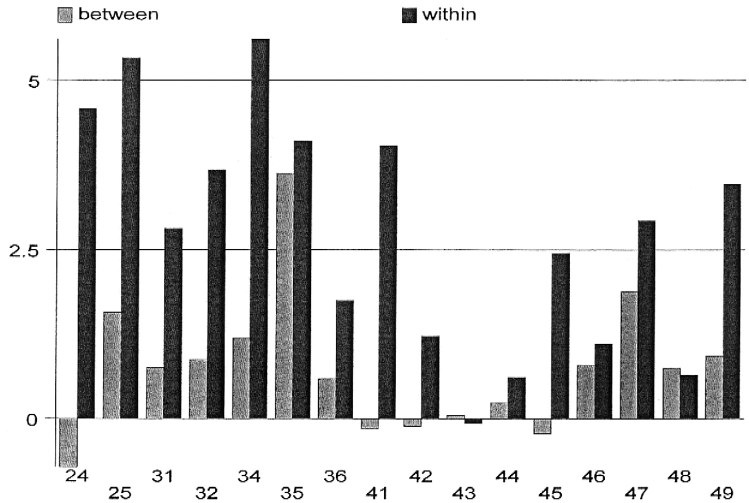

Fig. 1. Variation in the share of white collar by industry.

in the proportions of managerial and clerical employment, its total contribution to the changes in occupational structure is trivial.

Nevertheless, it is noteworthy that changes in occupational structure are very different across industries, and therefore the contribution of the different industries to the overall changes is very dissimilar. In Figs. 1 and 2, we show bar charts by industry of within and between firms changes in the shares of white collar and its

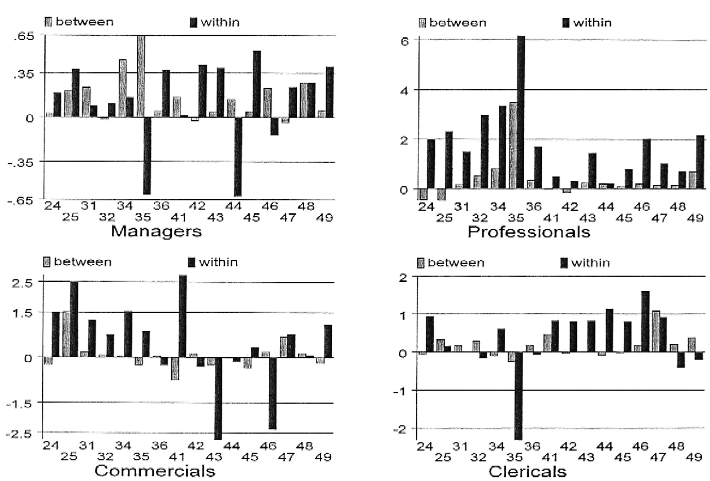

Fig. 2. Variation in occupation shares by industry.

disaggregated occupations.[8] Again, with a few exceptions, we resemble the evidence that within-firms changes constitute the main source of occupational shifts. But the most striking fact is the sharp differences in these shifts across industries. For instance, we observe that the electronic industry experienced the largest change in professionals, yet this shift is accompanied by a drop in managers and clericals. Unlike the uprising trend in commercials, basic textile and wood industries show a large drop in the share of commercials. This heterogeneity across industries point out the difficulties to explain changes in occupational structure: differences across industries have to do not only with the characteristics of technology, but also with the fact that a particular labor input (e.g., a professional or a commercial) can be very different across industries.

3.3. Capital structure and occupational shifts

We present some descriptive information from our main dataset in Table 4. In the first two rows of the upper panel we report the rates of growth of real output and total employment, which shows the fact that aggregate employment evolves accordingly to the movements in real output. In the following rows of the upper panel we also summarize the evolution of firms' net investments in the three capital inputs: physical capital, R&D capital, and technological capital externally generated to the firm,[9] as well as qualitative information about the adoption by firms of new capital inputs. Whereas investment in physical capital seems relatively unaffected by the shocks that firms face, there appears to be a positive correlation between firms' investments in R&D or technological capital and firms' productivity shocks.

However, although there exists a large number of firms that do not make use of R&D and technological capital inputs in their production process (about 90% of our sample in 1986), this number has been decreasing during the sample period. In Table 4, we observe that there has been a significant number of firms that introduce R&D or technological capital into the production process, that we denote as new innovative firms.[10] Whereas investments in R&D and technologi-

[8] We have exclude those industries with a small number of firms in the sample (nos. 22, 33 and 37–39).

[9] These last two variables are considered separately to distinguish between innovative capital based on search for innovations implemented by the firm and that based on successful innovations purchased by the firm but externally generated to it.

[10] Guarnizo and Guadamillas (1998) provide descriptive evidence on the features of R&D expenditures in Spain. The expenditures on external R&D dominates the expenditure on R&D activities within the firm, what reflects a significant degree of technological dependence. To a large extent, these activities generate process innovations consisting on adaptive technology aimed to improve the production process of existing products, rather than ultimate technology or new products. We should also stress the widespread use of marketing studies, concentrated on improvements in design, quality control, and standardization of existing products.

Table 4
Descriptive statistics (weighted averages)

Weighted means by year

	1987	1988	1989	1990	1991
Rates of growth					
Real output	8.28	7.83	7.82	0.06	0.04
Employment	1.65	1.88	1.87	−0.82	−2.21
Net investment rates					
Physical capital	5.23	5.98	5.92	6.41	6.15
R&D capital	31.37	23.00	19.96	16.50	17.56
Technological capital	20.71	17.32	16.83	15.92	11.97
Firms adopting new capital inputs					
R&D capital	28	15	21	51	46
Technological capital	15	15	11	23	7

Weighted annualized means by sign of aggregate shock and idiosyncratic shock

	Expansion (1987–1989)				Recession (1990–1991)			
	C	S	G	All	C	S	G	All
Net investment rates								
Physical capital	3.18	5.65	9.35	5.92	4.41	7.36	9.33	6.15
R&D capital	22.51	15.53	21.29	20.61	13.20	17.01	24.39	17.56
Technological capital	9.77	20.67	18.35	16.44	7.35	15.25	18.21	11.97
Firms adopting new capital inputs								
R&D capital	14	14	36	64	47	18	32	97
Technological capital	7	13	21	41	13	9	8	30
Within groups variations in shares								
White collar	0.791	0.717	0.203	0.542	1.427	0.462	0.426	0.944
Managers	0.178	0.024	−0.018	0.052	0.267	0.047	−0.275	0.078
Professionals	0.375	0.379	−0.083	0.201	0.482	0.237	0.908	0.531
Commercials	−0.045	0.195	0.410	0.209	0.560	0.024	0.030	0.298
Clericals	0.283	0.119	−0.116	0.080	0.117	0.155	−0.237	0.037
No. of observations	283	293	504	1080	462	299	319	1080

To define idiosyncratic shocks, firms have been classified into three groups according with their rate of change in total employment: Contracting(C), for values below −2%; Stable (S), for values between −2% and 2%; and Growing, for values above 2%.

cal capital are more intense when productivity shocks are more favorable to the firm, the number of new innovative firms reaches its maximum in 1990, precisely when firms face strongly negative shocks. This result is consistent with the reorganization of production during downturns, in line with Cooper and Haltiwanger (1993) and Caballero and Hammour (1994), among others. This evidence suggests that the variables indicating the introduction of R&D and technological capital into the production process can capture part of the qualitative decisions about reorganization of the production process. Given that the number of new innovative firms in our dataset is non-negligible, it may be possible to identify the effects of introducing new inputs in the production process.

In order to distinguish between aggregate and idiosyncratic shocks, and to establish the link between them, we have divided the sample period in accordance to the sign of aggregate shocks, establishing an expansion (1987–1989) and a recession period (1990–1991). In each of these two periods, we have classified firms according with three discrete states of their employment growth: contracting, stable, and growing.

We find that although the investment rate in physical capital is not sensitive to aggregate shocks, it depends positively on the idiosyncratic shocks faced by the firm. We also find that investment in R&D and technological capital is slightly procyclical, and tends to be higher in growing firms. In addition, the irruption of new innovative firms is strongly countercyclical,[11] yet there is not a clear pattern with respect to idiosyncratic shocks. We have also included the within-firms contribution to occupational shifts, from which we see that the within-firms change in the share of white collars is countercyclical, and the changes are larger for firms who are facing negative idiosyncratic shocks. This evidence suggests that firms are more prompted to reorganize their occupational structure when they face negative shocks, either aggregate or idiosyncratic, which, following Cooper and Haltiwanger (1993), can be explained by the fact that adjustment costs associated to reorganization of production are proportional to output, and therefore they will be over under downturns.

However, we find important differences when we disaggregate by white-collar occupations. In particular, we observe that the within-firm change in clericals is procyclical, these changes being more intense for firms who face negative idiosyncratic shocks. In contrast with this, we see that the share of managers tends to rise more for growing firms. In the case of professionals, contracting firms show an important increase irrespective of the aggregate shock, but the highest increase happens for growing firms during the recession period.

In Table 5, we provide preliminary evidence about the relationship between qualitative changes in capital structure and shifts in occupations. In order to consider different states in the process of new technology adoption, we have classified our sample of firms into three groups: new innovative firms, old innovative firms, and non-innovative firms. For each group, we report the net rates of job creation by occupation. Half the net creation of professional jobs have been made by new innovative firms. These firms have also contributed very signifi-

[11] In addition to the fact that the number of new innovative firms is higher in the recession period, the fact that the length of the expansion period is longer than the length of the recession period, reinforces the argument of countercyclical behavior for this decision.

Table 5
Net job creation by occupation and by firm according with their use of technological capital

	Non-innovative firms[a]	Old innovative firms[b]	New innovative firms[c]
Managers			
No. of jobs created	128	19	123
Jobs created per firm	0.2	0.1	0.7[†]
Avg. net job creation rate	8.3	1.8	18.7
Professionals			
No. of jobs created	706	528	1122
Jobs created per firm	0.9	3.4	6.3[‡]
Avg. net job creation rate	11.4	5.9	28.3
Commercials			
No. of jobs created	−6	1206	570
Jobs created per firm	0.0	7.9[‡]	3.2[‡]
Avg. net job creation rate	−0.1	27.8	19.5
Clericals			
No. of jobs created	280	−45	−206
Jobs created per firm	0.4	−0.3	−1.2
Avg. net job creation rate	3.2	−0.6	−3.5
Blue collars			
No. of jobs created	−3822	−3955	−1519
Jobs created per firm	−5.1	−26.0[‡]	−8.5
Avg. net job creation rate	−7.1	−12.4	−6.3
Firms' distribution	749	152	179

Difference with non-innovative firm.

[a] Non-innovative firms: never invest in R&D or technological capital.

[b] Old innovative firms: already used R&D or technological capital in 1986.

[c] New innovative firms: introduced R&D or technological capital in 1987–1991.

[†] Significant at the 5% level.

[‡] Significant at the 1% level.

cantly to the creation of commercial jobs. Old innovative firms are the ones who have created more commercial jobs, but its contribution to the creation of professional employment is much smaller than the one of new innovative firms. Non-innovative firms have been destroying commercial jobs, and creating a relatively small amount of professional jobs. The eradication of blue collar jobs seems very similar for these three groups of firms; what is consistent with the smoothness of job destruction. Finally, the evidence for clerical employment is significantly different to the one for the other white-collar occupations. Since clerical jobs represent more than one third of white collar jobs, this result shows that a simple classification of occupations in white collars and blue collars can underestimate the relationship between changes in capital structure and skill upgrading of the labor force.

4. The specification and estimation results

4.1. The empirical model

Our model is based on a system of factor demand equations for a competitive firm that produces an homogeneous good according to a particular technology; such technology is discontinuous whenever technological capital is zero. This discontinuity stems from the restructuring requirements that the firm should perform when it incorporates such input to the production schedule, so that the productivity of the different inputs are affected by the adoption of technological capital. The firm faces adjustment costs in two instances: in the intensive margin, changes in the stocks of existing inputs are costly; in the extensive margin, the firm faces costs of reorganization after the adoption of new inputs.

Every period, each firm determines its factor demands so as to minimize its expected discounted stream of current and future costs, conditional on the level of output, taking as given its technology, adjustment costs, stocks of inputs at the beginning of the period, and output and input prices. Under the assumptions that technology and adjustment cost functions are additive time separable, and that firms know current prices and technological shocks but faces uncertainty about prices and technological shocks in the future, the model is a Markov decision model where *conditional factor demands*[12] are functions of the level of output, the stocks of inputs at the beginning of the period, output and input prices, and current technological shocks.

One common problem for the empirical implementation of factor demand functions is the lack of reliable measures of some input prices, particularly in the case of technological capital, since it is difficult to construct a deflator for R&D or technological capital. In general, for most inputs — and most especially for capital inputs — there are only, if anything, aggregate deflators, and therefore the identification of price effects can be very poor. To overcome this problem, most empirical studies have exploited the covariation among the demand for different labor and capital inputs to identify input substitutability. This approach is based on solving for capital prices in the capital input demands and substitute them into the

[12] We denote the optimal demands resulting from the cost minimization problem as conditional factor demands (for a given output level), in contrast with ordinary factor demands which result from the profit maximization problem. The main difference between these functions is that price effects in conditional demands just capture pure substitution effects, whereas price effects in ordinary demands also capture the effect on the optimal output level.

labor input demands, obtaining a specification that excludes prices of capital inputs.

We also apply this strategy, although we adopt a more general specification that accounts for the existence of a discontinuity in factor demands. Letting D_{it} be the indicator for the use of new technological capital by firm i at period t, and $x_{it} = (l'_{it},\ k_{it},\ r_{it})'$, the vector of logarithms of the stocks of labor inputs $\boldsymbol{l}_{it}$, physical capital k_{it}, and technological capital r_{it}, and denoting the vector of the logarithm of prices of labor inputs as $\boldsymbol{w}_{it}$ and the logarithm of output as y_t, we can write the conditional demand for labor input j as

$$\boldsymbol{l}^j_{it} = \beta^j_0 + \beta^j_D D_{it} + \beta^j_l x_{i,t-1} + \beta^j_w \boldsymbol{w}_{it} + \beta^j_k k_{it} + \beta^j_r r_{it} + \beta^j_y y_{it} + \beta^j_\epsilon \epsilon_{it} \tag{3}$$

For simplicity, and to overcome collinearity problems, we have considered that the effect of adopting the new technology is just a constant shift (different for each input) in the demands of the different inputs. That is, price elasticities and dynamic interactions are not affected. Furthermore, we have assumed that adjustment costs are separable among labor and capital inputs.

Our specification for the unobservables for each labor input j can be written as follows,

$$\beta^j_\epsilon \epsilon_{it} \equiv \epsilon^j_{it} = \eta^j_i + \delta^j_{(i)} t + \Lambda^j_t + u^j_{it} \tag{4}$$

where for each firm i and each input j, η^j_i represents unobservable firm-specific time invariant effects; $\delta^j_{(i)}$ is the parameter associated to the industry trend in the demand of input j; Λ^j_t is the aggregate shock in the demand of input j at period t; and u^j_{it} is an idiosyncratic shock.

Controlling for endogeneity due to time-invariant firm-specific effects is particularly important. For instance, some firms may be using more professional workers and more technological capital than average because of unobserved firm-specific technological characteristics. If we ignore these effects, we would obtain biased estimates for the complementarity among labor and capital inputs. We remove these firm-specific effects taking first differences in Eq. (3), what yields the following equation for each labor input j:

$$\begin{aligned}\Delta \boldsymbol{l}^j_{it} = {} & \beta^j_D \Delta D_{it} + \beta^j_X \Delta x_{i,t-1} + \beta^j_w \Delta \boldsymbol{w}_{it} + \beta^j_K \Delta k_{it} + \beta^j_R \Delta r_{it} + \beta^j_Y \Delta y_{it} \\ & + \delta^j_{(i)} + \Delta \Lambda^j_t + \Delta u^j_{it}\end{aligned} \tag{5}$$

where both $\delta^j_{(i)}$ and $\Delta \Lambda_t$ are treated as parameters to estimate. The parameters $\delta^j_{(i)}$ represent industry-specific trends characterizing shifts in input demands, for which we control by including industry dummies. The parameters in $\Delta \Lambda_t$ represent aggregate shocks common to all firms, which can be captured by introducing time dummies.

If the idiosyncratic shocks u_{it}^{j} are uncorrelated over time, then Δu_{it}^{j} will be uncorrelated with $x_{i,t-2}$, $D_{i,t-2}$, $y_{i,t-2}$ and previous lags of these variables. In general, if u_{it}^{j} follows an MA(q) process, $x_{i,t-2-q}$, $D_{i,t-2-q}$, $y_{i,t-2-q}$ and previous lags will be valid instruments. Therefore, the key issue for identification of the model is the degree of autocorrelation in the idiosyncratic shocks u_{it}^{j} and the autocorrelation in labor and capital inputs. If adjustment costs are important (so that the stocks of inputs will by highly autocorrelated over time) and idiosyncratic shocks are not too persistent, identification is possible. We estimate the equations in (5) using the GMM estimator proposed by Arellano and Bond (1991). In order to test the validity of the sets of instruments we use the Hansen–Sargan test of over-identifying restrictions and a test of second-order serial correlation in Δu_{it}^{j}.

We observe in our sample a significant group of firms that do not employ professional or commercial workers at some period. However, an important proportion of these firms have introduced these inputs during the sample period. For these firms, we can estimate Eq. (5) using only the subsample of observations where the input has been employed at two consecutive periods. In principle, this might introduce a sample selection bias in our estimates for these labor inputs. However, once a firm has decided to employ these labor inputs, there is a very strong persistence in their utilization (e.g., the transition probability for the dummy that represents the use of commercial or professional workers is 0.96). This indicates that this selection problem is not very important in our sample. In other words, it seems that the decision of adopting a new labor input is not the result of a transitory shock, but that it is associated with a shift in the fixed-effect, which disappears when we take first differences.

4.2. Estimation results

We present the estimates for the equations of labor and capital inputs. Given that our data distinguish between R&D capital (based on firm's expenditures for search innovations), and technological capital (based on successful innovations externally generated and purchased by the firm), we consider them as different capital inputs. Furthermore, we also consider two indicators of technology adoption associated with a positive stock of each of these capital inputs. Given that the reorganization associated with the adoption of technological capital may take some time for the firm, we consider indicators of technology adoption at the former period. Given the lack of firm-level information on wages for each labor input, we include an industry-level measure of the relative wage of white collars with respect to blue collars. In the instrument set we have included all the strictly exogenous variables (industry-specific variables) as well as the lagged values of all the predetermined variables from $t-2$ to $t-4$.

Before presenting our preferred estimates of the system of equations characterized by (5), in Table 6 we show the estimates of the labor inputs equations based on the usual static specification without indicators for new technology adoption. Our results are not directly comparable with previous studies (since white collars are disaggregated into occupations, and our dependent variables are the logarithms of labor inputs instead of the logarithms of its shares). To interpret our estimates in the same manner as earlier studies, we should look at the relative effects of variables among different occupations. With the exception of clericals, we can see that the estimated elasticities with respect to physical capital (relative to blue collar) have a sign contrary to expected (in the case of managers and commercials), or are fairly small (in the case of professionals). Moreover, the elasticities with respect to R&D and technological capital are not significant, except for managers. In any case, the specification tests, particularly the Arellano–Bond test of second-order autocorrelation, provide evidence against these restricted equations for most of the white-collar inputs, suggesting that the implicit assumption of zero adjustment costs in labor inputs is not appropriate.

Table 6
Estimated elasticities with respect to real output, wages, and capital inputs based on static specification

	Managers	Professionals	Commercials	Clericals	Blue collars
Real output	0.108 (0.082)	−0.034 (0.095)	0.136 (0.138)	−0.082 (0.101)	0.103 (0.117)
Relative wage of white collars	−0.046 (0.084)	−0.124 (0.128)	−0.071 (0.256)	−0.067 (0.128)	0.087 (0.129)
Stocks of capital inputs					
Physical capital	0.161 (0.076)	0.320 (0.113)	0.126 (0.156)	0.393 (0.096)	0.289 (0.121)
R&D capital	−0.027 (0.024)	0.010 (0.027)	0.027 (0.031)	−0.018 (0.028)	0.049 (0.031)
Technological capital	0.171 (0.061)	0.089 (0.051)	0.022 (0.059)	−0.019 (0.049)	−0.136 (0.072)
Wald tests					
Time dummies	2.53 (0.64)	8.18 (0.08)	2.24 (0.69)	9.30 (0.05)	3.65 (0.46)
Industry dummies	19.11 (0.45)	30.58 (0.04)	29.51 (0.04)	24.30 (0.19)	66.41 (0.00)
Hansen–Sargan test	29.11 (0.71)	42.46 (0.41)	42.69 (0.40)	43.98 (0.12)	44.79 (0.32)
m_2 test (second order autocorrelation)	−1.78 (0.08)	−2.10 (0.04)	−1.98 (0.05)	−1.47 (0.14)	−1.11 (0.27)
No. of observations	4320	3687	2317	4320	4320
No. of companies	1080	962	637	1080	1080

Dependent variable: logarithm of labor input. GMM estimation in first differences.

Table 7
Short-run elasticities of labour inputs

	Managers	Professionals	Commercials	Clericals	Blue collars
Lagged input	0.841 (0.053)	0.232 (0.032)	0.044 (0.017)	0.559 (0.033)	0.610 (0.033)
Real output	0.093 (0.049)	−0.138 (0.064)	−0.161 (0.081)	0.128 (0.052)	0.186 (0.057)
Relative wage of white collars	0.022 (0.090)	−0.209 (0.127)	−0.452 (0.221)	−0.084 (0.113)	−0.015 (0.111)
Stocks of capital inputs					
Physical capital	0.040 (0.052)	0.296 (0.088)	0.102 (0.109)	0.049 (0.063)	0.118 (0.074)
R&D capital	−0.025 (0.015)	0.002 (0.019)	0.031 (0.021)	−0.008 (0.017)	0.065 (0.017)
Technological capital	0.059 (0.036)	0.017 (0.034)	−0.005 (0.034)	0.032 (0.032)	−0.015 (0.032)
Introduction of new inputs					
R&D capital	0.065 (0.063)	0.008 (0.074)	−0.002 (0.073)	0.005 (0.074)	−0.001 (0.063)
Technological capital	−0.005 (0.115)	0.031 (0.127)	0.171 (0.116)	−0.095 (0.104)	−0.469 (0.125)
Wald tests					
Time dummies	1.22 (0.87)	26.18 (0.00)	11.71 (0.02)	2.51 (0.64)	11.71 (0.02)
Industry dummies	15.61 (0.68)	51.66 (0.00)	38.9 (0.00)	18.99 (0.46)	33.06 (0.02)
Hansen–Sargan test	100.43 (0.66)	133.53 (0.10)	102.73 (0.77)	129.42 (0.15)	92.84 (0.93)
m_2 test (second order autocorrelation)	0.03 (0.98)	−1.29 (0.19)	−1.79 (0.07)	−0.03 (0.98)	−0.63 (0.53)
No. of observations	4320	3687	2317	4320	4320
No. of companies	1080	962	637	1080	1080

Dependent variable: logarithm of labor input. GMM estimation in first differences.

In Table 7, we present the main estimation results for the labor inputs equations, and the analogous equations for capital input demands are reported in Table 8. The dependent variable in each equation is the logarithm of the stock of the corresponding input. The Hansen–Sargan test cannot reject the over-identifying restrictions in all the estimated equations except for physical capital.[13] With

[13] The evidence against model specification for physical capital can be due to the existence of more complex dynamics not captured by the model. Such dynamics could be attributed both to irreversibilities or lump-sum adjustment costs for capital investment, and to differences in the efficiency of different capital vintages.

Table 8
Short-run elasticities of capital inputs

	Physical	R&D	Technological
Real output			
	0.038 (0.028)	0.165 (0.054)	0.447 (0.038)
Stocks of lagged capital inputs			
Physical capital	0.805 (0.033)	−0.190 (0.137)	−0.602 (0.069)
R&D capital	0.018 (0.010)	0.122 (0.010)	−0.110 (0.017)
Technological capital	0.009 (0.012)	0.051 (0.033)	0.188 (0.006)
Stocks of lagged labor inputs			
Managers	0.058 (0.029)	0.423 (0.091)	−0.032 (0.035)
Professionals	−0.007 (0.014)	−0.142 (0.058)	0.365 (0.035)
Commercials	0.014 (0.011)	−0.036 (0.038)	0.162 (0.023)
Clericals	0.006 (0.014)	−0.060 (0.056)	0.146 (0.042)
Blue collars	−0.002 (0.011)	−0.400 (0.071)	0.201 (0.042)
Temporary	0.004 (0.005)	−0.065 (0.011)	0.039 (0.007)
Wald tests			
Time dummies	32.17 (0.00)	2.60 (0.63)	51.18 (0.00)
Industry dummies	45.92 (0.00)	186.54 (0.00)	1884.07 (0.00)
Hansen–Sargan test			
	171.33 (0.00)	112.01 (0.14)	114.48 (0.27)
m_2 test (second order autocorrelation)			
	−0.28 (0.78)	0.10 (0.92)	−0.01 (0.99)
No. of observations	4320	646	466
No of companies	1080	214	143

Dependent variable: log of capital inputs. GMM estimation in first differences.

the exception of commercials, the Arellano–Bond test of second-order autocorrelation also presents strong evidence in favor of the specification.

The first noticeable thing in Table 7 is that the lagged endogenous variable shows a positive and very significant effect in all the estimated equations. Since we are controlling for individual heterogeneity, this evidence points out the importance of adjustment costs in input demand decisions, and confirms the source of specification error pointed out by the autocorrelation tests in Table 6. Nevertheless, the size of the coefficients differs very much across occupations, what points out that inertia in the stock of labor inputs are very different.

The elasticities with respect to physical capital are positive for all permanent labor inputs, though they are small and insignificant, except in the demand for professionals. In fact, the difference in this elasticity between professionals and blue collars goes from 0.031 in the static model to 0.178 in the dynamic model, showing the serious downward bias associated with the static specification. Most of the estimated elasticities with respect to R&D capital and technological capital are small and very imprecise. Therefore, our results based on firm-level data highly disaggregated by occupations resemble the puzzle from previous empirical work that estimated elasticities with respect to the different capital inputs are surprisingly small. In addition, the cross effects among labor inputs, which are presented in Appendix B, are small and insignificant in most cases.

The estimated coefficients for the indicators of adoption of R&D are small and insignificant for all permanent labor inputs. By contrast, we find a strongly positive effect of the adoption of technological capital on the demand for commercials, and a significant but opposite effect for blue collar. Although the precision of these estimates is not too high, this result highlights that the introduction of technological capital is a much more relevant indicator of production reorganization than the introduction of R&D capital. The reason seems to be straightforward: whereas R&D capital is based on firms' expenditures on search for innovations (so that reorganization of production after the introduction of R&D will occur only if innovations are successfully generated), technological capital is based on firms' purchases of successful innovations, what makes reorganization of production more likely. It becomes apparent that the indicator of introducing new technological capital has a larger effect than an increase in such input once it had been introduced in the past. This result is also consistent with our preliminary evidence in Table 5, where we obtained huge differences in the job creation of commercial jobs for new innovative firms and non-innovative firms. Both the magnitude and significance of the effects associated to the introduction of new inputs are very robust to changes in the sets of instruments and explanatory variables. Our results are in favor of the non-neutrality of some types of reorganization of production over occupational structure. In particular, the reorganization in the production schedule after the introduction of technological capital have exerted an important reduction in the demand for blue collars and a rise in the demand for commercials.

The elasticities of labor inputs with respect to real output confirm the evidence of negative correlation between shares for professional and commercial workers and output growth found in Section 3.3, and the opposite for blue collars. A 1% increase in real sales implies, in the short-term, a reduction of 14% and 16% for professional and managers, and a 19% rise for blue collars. We also find positive short run elasticities for managers, and most especially, for clericals. This last input also showed a negative although insignificant coefficient for the adoption of technological capital. Notice that the effect of the output level differs significantly among labor inputs. It therefore appears that the optimal occupational composition varies with the output level, thus suggesting the existence of non-homotheticities in the production function.

We also find that the elasticities with respect to the relative wage of white collars have the expected sign for three of the white-collar inputs (professional, commercial, and clerical), but it is only significant in the case of commercials. This lack of significance can be probably attributed to the lack of firm-level variability for this measure.

In Table 8, we find interesting feedback effects of employment occupational structure on capital investment decisions. In particular, the lagged stocks of white-collar inputs have positive effects on the demand for technological capital, which are significant in most cases. We also find a positive and significant effect of managers on the demands for physical and R&D capital. Moreover, the effect of blue collars is strongly negative and significant for R&D capital. These effects provide evidence of feedback effects between labor inputs and capital inputs, suggesting that the observed tendency in occupational structure (a shift towards white-collar occupations) may have anticipated growths in physical capital and technological capital. However, although these feedback effects are significant, they are not very large. Another interesting result is that the short run elasticities of technological capital inputs with respect to lagged physical capital are negative and significant, what suggests a certain degree of substitutability of the former inputs with respect to physical capital. Finally, the positive and significant coefficients on real output for R&D and technological capital inputs are also consistent with the previous evidence in subsection 3.3 that investments in these two capital inputs are positively correlated with output growth: particularly, we find a short run elasticity of 45% for technological capital.

The fact that the lagged endogenous variables have significantly positive effects on the demands for the different inputs stress the relevance of the dynamics in such demands. This result implies that the demand elasticities of white-collar inputs (relative to blue collar) implied by our estimates are, in absolute terms, significantly higher in the long run than in the short run. However, despite that there is evidence of feedback effects between labor and capital inputs, these effects are small, so that accounting for them does not entail important differences in the implicit long-run elasticities (not reported here).

In any case, the most remarkable evidence is that the most important elasticities for all white-collar occupations, relative to blue collar, are the ones associated with the introduction of technological capital, both in the long- and short run. Such elasticities are quite similar in the long- and short run, what indicates that almost all the effect is contemporaneous. This confirms the importance of this kind of reorganization of the production process over changes in occupational structure.

5. Conclusions

This study is concerned with the phenomenon of technological change biased towards certain white-collar occupations occurred in most OECD countries during the 1980s. Our data consist of a balanced panel of 1080 manufacturing firms along the period 1986–1991 containing information on five different labor inputs, physical capital stock and R&D and technological capital. The fact that we have disaggregated information on white collar employees by four occupations makes possible to consider firm's behavior in the demands for different white-collar occupations. We explore alternative explanations to the results from Dunne et al. (1995), among others, which found that although capital and technological capital have significant effects on the skill composition of the workforce, they leave most of the secular and cyclical variation unexplained.

Our main hypothesis is that the adoption by a firm of new technological capital entails a deep reorganization of the workplace, which is usually complementary with high skilled labor. As discussed earlier, there exist huge informal evidence about the kind of restructuring processes lived by Spanish firms in the last two decades. We also consider other complementary hypotheses, as the existence of dynamic feedback effects between occupational structure and capital stocks and non-homotheticities in the production function, which may make the optimal skill mix to depend on the level of output. In order to provide evidence about our main hypothesis, it is crucial to have firm-level data on discrete decisions of introducing new inputs, in addition to the continuous decisions on changing the amounts of the existing inputs.

Our results can be summarized as follows. First, we find that the main changes in occupational structure become more intense when firms face negative shocks. Furthermore, whereas the intensity of investment in technological capital increases when firms face positive shocks, the propensity of a firm to adopt new technological capital rises as firms face negative shocks. This evidence favors the theory about the optimality of restructuring during downturns. Second, at the firm level, there appear significant differences between the effects on occupational structure of the continuous decision of increasing the stock of technological capital and the discrete decision of introducing technological capital by first time. In particular, we observe that the introduction of new technological capital into the production process contributes to explain sizable changes in occupational structure. In contrast, the introduction of R&D capital has no significant effect, which we attribute to the fact that, contrary to technological capital, R&D capital does not measure unambiguous introduction of successful innovations. This evidence, and the fact that changes in occupational structure become more intense when firms face negative productivity shocks, confirm our preliminary descriptive evidence on the optimality of restructuring during recessions. Third, we find an important persistence in the demands for most labor and capital inputs, pointing out the quasi-fixed nature of such inputs. This implies that elasticities are much larger in the long run than in the short run. Finally, the variables associated with occupational structure have significant effects on capital inputs, although such effects are small and therefore, the capital–labor feedback effects are unimportant in the long run.

The results thus provide important evidence favoring the idea that the non-marginal decision of introducing a new input into the production process has a different and stronger effect than increasing the amount of an input that was already used in production. We also find that the frequency of firms undertaking such non-marginal decisions is higher when they face negative productivity shocks, what is consistent with those theories that predict reorganizations of the production process during downturns. Our results emphasize the importance of firm-level panel data with a high disaggregation of production inputs, like the one we use, to study the determinants of changes in occupational structure. The availability of datasets containing more detailed and disaggregated information about the introduction of new capital inputs and some other variables capturing the reorganization of the production process will allow to implement a more direct test of the reorganization hypothesis.

Appendix A. Data Description

A.1. Construction of the CBBE data set

The CBBE data set is a balanced panel of 1080 Spanish non-energy, manufacturing companies, with a public share lower than 50%, recorded in the database of the Bank of Spain's Central Balance Sheet Office. This dataset was started in 1982 collecting data on firms of large relative size (and hence, oversampling larger firms). However, the tendency in subsequent years has been characterized by the addition of firms of smaller relative size. The firms included in this data base represent almost 40% of the total Value Added in Spanish manufacturing. Although this database contains firm-level information on the balance sheets, employment, and other complementary information for a large number of manufacturing companies since 1982, disaggregated data on employment are reported only between 1986 and 1991. We have thus selected those firms that remained in the sample during 1986–1991, and satisfied several coherency conditions. All companies with non-positive values for net worth, capital stock, accumulated and accounting depreciation, labor costs, employment, sales, output, or whose book value of capital stock jumped by a factor greater than 3 from one year to the next, were dropped from the sample.

Table A1 presents the distribution of firms in this balanced panel by size (measured as the time average of firm's employees) and by two-digit industries. The total number of employees at these firms is around 180,000, that represents approximately 8% of total Spanish manufacturing employment during this period.

We have also used a complementary dataset to obtain wages for blue collar and white collar jobs. The CBBE dataset reports the firm's average wage rate for total employees, though the wage rate for each labor input is not reported. Information on average wages for white collar and blue collar employees is reported by the Encuesta de Salarios (Source: Spanish National Institute of Statistics, INE). This survey provides three-digit industry-level information about wage rates in an annual basis, irrespective of the contract duration.

Table A1
Distribution of firms by two-digit industry and by size (balanced panel 1986–1991; 1080 firms)

	Small	Med1	Med2	Large	Total
Iron, steel and metal (22)	1	4	3	2	10
Bldg. materials (24)	12	38	21	17	88
Chemicals (25)	15	42	39	54	150
Non-ferrous metal (31)	15	55	22	16	108
Basic machinery (32)	13	27	22	13	75
Office machinery (33)	0	0	0	1	1
Electric materials (34)	3	14	15	23	55
Electronic (35)	1	2	7	6	16
Motor vehicles (36)	2	12	12	14	40
Shipbuilding (37)	0	3	1	2	6
Other motor vehicles (38)	0	1	4	3	8
Precision instruments (39)	1	1	0	2	4
Non-elaborated food (41)	22	39	26	25	112
Food, tobacco, and drinks (42)	23	22	15	20	80
Basic textile (43)	11	19	24	22	76
Leather (44)	2	9	7	3	21
Garment (45)	4	22	20	10	56
Wood and furniture (46)	6	18	13	6	43
Cellulose and paper edition (47)	8	25	18	15	66
Plastic materials (48)	9	13	16	4	42
Other non-basic (49)	4	8	6	5	23
Total	152	374	291	263	1080

The size variables are referred to the firm's time average of total employment. Small denotes employment lower or equal than 25. *Med1* denotes employment between 25 and 75; *Med2* denotes employment between 75 and 200; and *Large* for employment larger than 200.

A.2. Construction of variables

A.2.1. Employment

Number of employees is disaggregated in permanent white collar, permanent blue collar, and temporary employees. Permanent white-collar employment is also disaggregated into four occupations: managerial, professional, commercial, and clerical. To maintain measurement consistency, number of temporary employees is calculated in annual terms by multiplying the number of temporary employees along the year times the average number of weeks worked by temporary employees and divided by 52.

A.2.2. Output

Gross output at retail prices is calculated as total sales, plus the change in finished product inventories and other income from the production process, minus taxes derived on the production (net of subsidies).

A.2.3. Physical capital

We are interested in depreciable physical capital (which is already productive), so Land and Capital stock in the course of construction are excluded from the definition of physical capital. Since the CBBE does not have independent estimates of investment available, gross nominal investment I_{it} must be imputed from changes in the book value of physical capital with a correction for depreciation, that is $I_{it} = \mathrm{KNB}_{it} - \mathrm{KNB}_{i,t-1} + \mathrm{Dep}_{it} + \mathrm{Rev}_{it}$ where, $\mathrm{KNB}_{it} = \mathrm{KGB}_{it} - \mathrm{ADep}_{it}$ is the book value of the net stock of physical capital (book value of the gross stock of physical capital KGB_{it} minus accumulated depreciation ADep_{it}); Dep_{it} is the accounting depreciation during the year; and Rev_{it} is the net variation in the book value of physical capital and in its accumulated depreciation due to positive and/or negative revaluations.

To calculate the replacement value of capital, we use a perpetual inventory method which takes account for depreciation and inflation. To do this, an initial value for the first year that data is available for a given firm is calculated as $q_1 K_{i1} = (q_1/q_{1-\mathrm{AA}_i}) \times \mathrm{KGB}_{it}(1-\delta_i)^{\mathrm{AA}_i}$ where q_t is the price deflator of the stock of physical capital at year t; δ_i is the average depreciation rate of the stock of physical capital; and AA_i is the average age of the stock of physical capital, which is approximated by the ratio $\mathrm{ADep}_{i1}/\mathrm{Dep}_{i1}$ for the first year in which data for the firm are available. Furthermore, the average depreciation rate is computed at the firm level as the ratio of firm's average accounting depreciation to the firm's average accumulated depreciation. As regards price indices, the corresponding GDP implicit deflator of investment goods is used (Source: INE). The recursive method to compute the replacement value of the stock of physical capital from the second year that data is available is $q_t K_{it} = (q_t/q_{t-1}) \times K_{i,t-1}(1-\delta_i) + I_{it}$, which assumes that investment occurs at the end of the year.

A.2.4. R&D and technological capital stocks

The CBBE data report data on R&D investment, defined as the firm's expenditures on search for innovations, and investment in technological capital, defined as the firm's expenditures on successful innovations externally generated to the firm. We treat these two variables as separate items. Since the stocks of these R&D and technological capital are unknown, to construct the corresponding stocks we assume, following Hall and Mairesse (1995), a depreciation rate for both stocks of 15% and a presample growth in real investment of 5%. Therefore, the stocks of R&D and technological capital, for the first year in which data are available, KRD_{i1} and Ktec_{i1}, are calculated as $\mathrm{KRD}_{it} = \mathrm{RD}_{i1}/(0.05 + 0.15)$ and $\mathrm{Ktec}_{i1} = \mathrm{Rtec}_{i1}/(0.05 + 0.15)$, where RD_{it} and Rtec_{it} are the firm's investments in R&D and technological capital at period t. From the subsequent years, we compute the stocks of R&D and technological capital using a perpetual inventory method. As the price index, we use the Retail Price Index at the two-digit industry level.

Appendix B. Complementary estimates

Table A2. Short-run cross dynamic effects among labor inputs.

	Managers	Professionals	Commercials	Clericals	Blue collars
Managers		−0.031	−0.216	0.051	0.063
		(0.072)	(0.072)	(0.051)	(0.060)
Professionals	0.020		0.065	−0.025	0.007
	(0.022)		0.065	−0.025	0.007
Commercials	−0.010	−0.015		0.013	0.037
	(0.018)	(0.023)		(0.020)	(0.021)
Clericals	0.012	0.020	−0.015		0.034
	(0.022)	(0.034)	(0.035)		(0.027)
Blue collars	−0.040	−0.017	0.116	0.010	
	(0.052)	(0.023)	(0.032)	(0.023)	
Temporary	−0.012	−0.009	−0.003	0.000	−0.015
	(0.009)	(0.014)	(0.013)	(0.010)	(0.011)

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